CHAPTER 1

Brain-Computer Music Interfacing: Interdisciplinary Research at the Crossroads of Music, Science and Biomedical Engineering

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Abstract:
Research into Brain-Computer Music Interfacing (BCMI) involves three major challenges: the extraction of meaningful control information from signals emanating from the brain, the design of generative music techniques that respond to such information and the definition of ways in which such technology can effectively improve the lives of people with special needs and address therapeutic needs. This chapter discussed the first two challenges, in particularly the music technology side of BCMI research, which has been largely overlooked by colleagues working in this field. After a brief historical account of the field, the author reviews the pioneering research into BCMI that has been developed at Plymouth University's Interdisciplinary Centre for Computer Music Research (ICCMR) within the last decade or so. The chapter introduces examples illustrating ICCMR's developments and glances at current work informed by cognitive experiments.

1.1 Introduction

Until recently, developments in electronic technologies have seldom addressed the well being of people with special needs within the health and education sectors. But now BCMI research is opening up fascinating possibilities at these fronts. BCMI systems have the potential to be used as recreational devices for people with physical disability, to support music-based activity for palliative care, in Occupational Therapy, and indeed in Music Therapy, in addition to innovative applications in composition and music performance. It should be mentioned, however, that although I have an avid interest in developing assistive technology for medical and special needs, there are a number of potentially interesting artistic uses of BCMI technology beyond such applications.

Plymouth University's Interdisciplinary Centre for Computer Music Research (ICCMR) is a main protagonist of the field of BCMI. This chapter reviews the pioneering research we have been developing at ICCMR for over a decade. Our approach is hands-on orientated. We often start by dreaming scenarios followed by implementing proof-of-concept or prototype systems. Then, as

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we test these systems we learn what needs to be further developed, improved, discarded, replaced, and so on. These often lead to new dreamed scenarios and the cycle continues incrementally. In reality, as we shall see below, vision, practice and theory do not necessarily take place sequentially in our research.

This chapter begins with a brief discussion introduction to the field and approaches to BCMI. Then, it introduces two BCMI systems that my team and I have designed in response to two dreamed scenarios:

1) Would it be possible to play a musical instrument with signals from the brain? No hands used.
2) Would it be possible to build a BCMI system for a person with locked-in syndrome to make music?

Next, I briefly discuss what I have learned from building these systems and identify challenges for making further progress. I suggest that one of the pressing challenges of BCMI research is to gain a better understanding of how the brain processes music, with a view on establishing detectable meaningful musical neural mechanisms for BCMI control. Then, I present two experiments aimed at gaining some of such understanding: one addressing active listening and the other addressing tonal processing. Each experiment is followed by an introduction to work-in-progress prototypes that I developed in response to the dreamed scenarios that emerged from the experiments.

1.2 Background to BCMI

Human brainwaves were first measured in the mid of 1920s by Hans Berger (1969). Today, the EEG has become one of the most useful tools in the diagnosis of epilepsy and other neurological disorders. In the early 1970s, Jacques Vidal proposed to use the EEG to interface with a computer in a paper entitled *Toward Direct Brain-Computer Communication* (Vidal 1973). Many attempts at using the EEG as a means to interface with machines followed with various degrees of success; for instance, in early 1990s Jonathan Wolpaw and colleagues developed a prototype of a system that enabled primitive control of a computer cursor by subjects with severe motor deficits (Walpaw et al. 1991).

As for using EEG in music, as early as 1934 a paper in the journal *Brain* had reported a method to listen to the EEG (Adrian and Matthews 1934). But it is now generally accepted that it was composer Alvin Lucier who composed the first musical piece using EEG in 1965: *Music for Solo Performer* (Lucier 1976). Composers such as Richard Teitelbaum (1976), David Rosenboom (1976) and a few others followed with a number of interesting ideas and pieces.

The great majority of those early pioneers who have attempted to use the EEG to make music have done so by direct sonification of EEG signals. However, in 1990 David Rosenboom introduced a musical system whose parameters were driven by EEG components believed to be associated with shifts of the performer's selective attention (Rosenboom 1990). Rosenboom explored the hypothesis that it might be possible to detect certain aspects of our musical experience in the EEG signal. This was an important step for BCMI research as Rosenboom pushed the practice beyond the direct sonification of EEG signals, towards the notion of digging for potentially useful information in the EEG to make music with.

1.3 Approaches to Brain-Computer Music Interfacing

Research into Brain-Computer Interfacing (BCI) is concerned with devices whereby users voluntarily control a system with signals from their brain. The most commonly used brain activity signal in BCMI is the EEG, which stands for electroencephalogram. In such cases, users must steer their EEG in a way or another to control the system. This informs the hard approach to BCMI: a system whereby the user voluntarily controls music. However, it is arguable that voluntary control may not be always necessary for a music system. For instance, a music system may simply react to the mental states of the user, producing music that is not necessarily explicitly controlled. We shall refer to such systems as soft BCMI, as opposed to hard BCMI. In this chapter, however, we will give focus to hard BCMI: we are interested inactive, voluntary control of music. An example of passive soft BCMI is introduced in Chapter 13.

A hard BCMI system requires users to produce patterns of brain signals voluntarily to control musical output and this often requires training. Therefore playing music with a BCMI should normally require ability and learning. This can be attractive for many individuals; for example, as an occupational therapeutic tool for severe physical impairment.

In a previous paper we identified two approaches to control the EEG for a BCI: *conscious effort* and *operant conditioning* (Miranda et al. 2011). Conscious effort induces changes in the EEG by engaging in specific cognitive tasks designed to produce specific EEG activity (Curran and Stokes 2003; Miranda et al. 2005). The cognitive task that is most often used in this case is motor imagery because it is relatively straightforward to detect changes in the EEG of a subject imagining the movement of a limb such as, for instance, the left hand (Pfurtscheller et al. 2007). Other forms of imagery, such as, auditory, visual and navigation imagery, can be used as well.

Operant conditioning involves the presentation of a task in conjunction with some form of feedback, which allows the user to develop unconscious control of the EEG. Once the brain is conditioned, the user is able to accomplish the task without being conscious of the EEG activity that needs to be generated (Kaplan et al. 2005).

Somewhere in between the two aforementioned approaches is a paradigm referred to as evoked potentials, or event-related potentials, abbreviated as ERP. ERP occur from perception of a user to an external stimulus or set of stimuli. Typically ERPs can be evoked from auditory, visual or tactile stimuli producing auditory, visual and somatosensory evoked potentials respectively. An ERP is the electrophysiological response to a single event and therefore is problematic to detect in EEG on a single trial basis, becoming lost in the noise of ongoing brain activity. But if a user is subjected to repeated stimulation at short intervals, the brain's response to each subsequent stimulus is evoked before the response to the prior stimulus has terminated. In this case, a steady-state response is elicited, rather than left to return to a baseline state (Regan 1989).

For users with healthy vision and eye movements the Steady State Visual Evoked Potential (SSVEP) is a robust paradigm for a BCI. And it has the advantage that it does not require much training in order to be operated satisfactorily. Typically, the user is presented with images, or simple images, on a standard computer monitor representing actions available to perform with the

BCI; these could be, for instance, letters or geometrical figures. In order to make a selection users must simply direct their gaze at the image corresponding to the action they would like to perform. The images must have a pattern reversing at certain frequency. As the user's spotlight of attention falls over a particular image, the frequency of the pattern reversal rate can be detected in the user's EEG through basic spectral analysis. What is interesting here is that once the target signal is detected in the EEG, it is possible to classify not only a user's choice of image, but also the extent to which the user is attending it (Middendorf at al. 2000). Therefore, each target is not a simple binary switch, but can represent an array of options depending on the user's attention.

1.4 BCMI-Piano

The BCMI-Piano resulted from the first aforementioned dream: Would it be possible to play a musical instrument with signals from the brain? No hands needed.

Initially, we looked into translating aspects of the EEG onto musical notes played on a synthesiser. However, this strategy proved to be unsatisfactory. The system did not convey the impression that one was playing a musical instrument. The notes sounded as if they were generated randomly and the synthesised sounds lacked the auditory quality that one would expect to hear from an acoustic musical instrument.

In order to remediate this, we connected the system to a MIDI-enabled acoustic piano (Figure 1.1). That is, an acoustic piano that can be played by means of MIDI signals. MIDI stands for Musical Instrument Digital Interface. It is a protocol developed in the 1980's, which allows electronic instruments and other digital musical devices and software to communicate with each other. MIDI itself does not make sound. Rather, it encodes commands, such as 'note on,' 'note off', etc. In our case, MIDI commands controlled a mechanism built inside the piano that moved the hammers to strike the strings. This resulted in a system whereby a real piano is played with brain signals. The quality of the sound improved considerably. But still, we felt that the result was not convincingly musical: the output sounded almost as if the notes were generated randomly. If we were to demonstrate that it is possible to play music with brain signals, then system ought to do more than merely brainwave activity with notes. Ideally, the music should result from some form of musical thinking detectable in the EEG. But the task of decoding the EEG of a person thinking of a melody, or something along these lines, is just impossible with today's technology.

Thus, I came up with the idea of endowing the machine with some form of musical intelligence, which could be steered by the EEG. The big idea was to program the system with the ability to compose music on the fly, obeying simple abstract generic commands, which might be conveyed by something detectable in the EEG. This would not necessarily correlate to any musical thought at all, but it would at least be a realistic point of departure. For instance, I was aware that it is relatively straightforward to detect a pattern in the EEG, called Alpha rhythm, which is present in the EEG of a person with eyes closed and in a state of relaxation.

Thus, my team and I moved on to implement BCMI-Piano, a system that looks for information in the EEG signal and match the findings with assigned generative musical processes corresponding to distinct musical styles. We implemented an Artificial Intelligence system that is able to generate pieces of piano music in the style of classic composers, such as Schumann, Satie, Beethoven, Mozart, and so on. For instance, if the system detects prominent Alpha rhythms in the EEG, then it would activate assigned processes that generate music in the style of

Robert Schumann's piano works. Conversely, if it detected an EEG pattern other than Alpha rhythms, then it would generate music in the style of Ludwig van Beethoven's sonatas for piano.

Figure 1.1: With BCMI-Piano one can play music generated on the fly on a MIDI-enabled acoustic piano with brain signals. No hands needed.

After a few trials, we decided to use seven channels of EEG, which can be obtained with seven pairs of electrodes placed on the scalp, covering a broad area of the head. The signals were filtered in order to tear out signal interference (e.g., interference generated on electrodes near the eyes due to eye blinking) and added their signals together prior to executing the analyses. The system analyses the spectrum of the EEG and its complexity. The analyses yields two streams of control parameters for the generative music system: one, which carries information about the most prominent frequency band in the signal - popularly referred to as EEG rhythms - and another, which carries a measure of the complexity of the signal. The former was used to control algorithms that generated the music and the latter to regulate the tempo and the loudness of the music.

The most prominent EEG frequency band is obtained with a standard FFT (Fast Fourier Transform) algorithm and the measure of complexity is obtained with Hjorth's analysis (Hjorth 1970).

FFT analysis is well-known in BCI research and will be discussed in more detail in other chapters of this volume. Basically the system looks for two patterns of information in the spectrum of the EEG: Alpha and Beta rhythms. Alpha rhythms are strong frequency components in the signal between 8Hz and 13Hz and Beta rhythms are strong components between 14Hz and 33Hz.

The less familiar Hjorth's analysis it is a time-based amplitude analysis, which yields three measurements: activity, mobility and complexity. The signal is measured for successive epochs - or windows - of one to several seconds. Activity and mobility are obtained from the first and second time derivatives of amplitude fluctuations in the signal. The first derivative is the rate of change of the signal's amplitude. At peaks and troughs the first derivative is zero. At other points it will be positive or negative depending on whether the amplitude is increasing or decreasing with time. The steeper the slope of the wave, the greater will be the amplitude of the first derivative. The second derivative is determined by taking the first derivative of the first derivative of the signal. Peaks and troughs in the first derivative, which correspond to points of greatest slope in the original signal, result in zero amplitude in the second derivative, and so forth.

Amplitude fluctuations in the epoch gives a measure of activity. Mobility is calculated by taking the square root of the variance of the first derivative divided by the variance of the primary signal. Complexity is the ratio of the mobility of the first derivative of the signal to the mobility of the signal itself; for instance, a sinewave has a complexity equal to 1. Figure 1.2 shows an example of Hjorth analysis. A raw EEG signal is plotted at the top (C:1) and its respective Hjorth analysis is plotted below: activity (C:2), mobility (C:3) and complexity (C:4). The tempo of the music is modulated by the complexity measure.

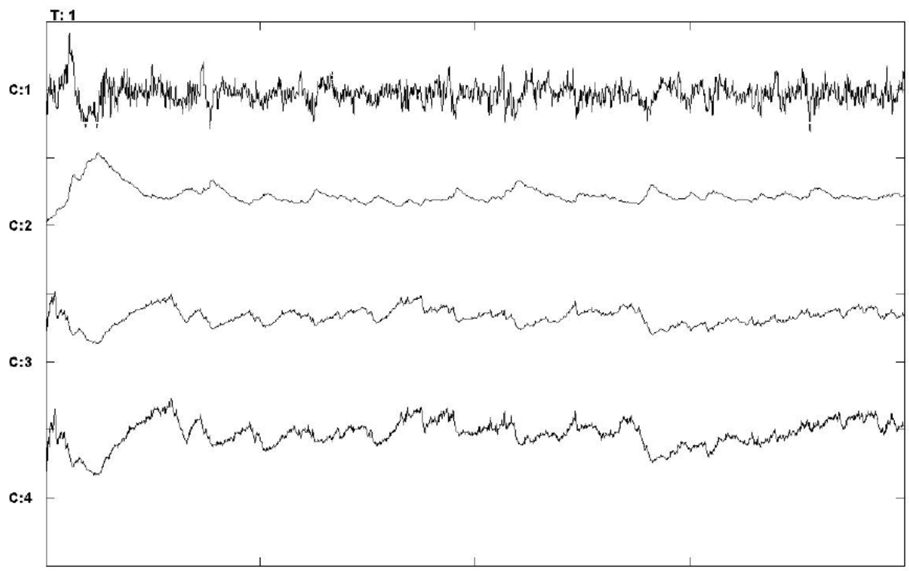


Figure 1.2. A typical example of Hjorth analysis of an EEG signal.

BCMI-Piano's music algorithm was developed with the assistance of Bram Boskamp, then a post-graduate student at ICCMR. It generates the music using rules that are deduced automatically from a given corpus of examples. It deduces sequencing rules and creates a transition matrix representing the transition-logic of what-follows-what. New musical pieces are generated in the style of the ones of the training corpus. Firstly, the system extracts blocks of music and deduces the rules from the given examples. Then it sequences those blocks in a domino-like manner based on the deduced rules (Miranda and Boskamp 2005).

Every time the system is about to produce a measure of music, it checks the power spectrum of the EEG at that moment and triggers the generative music instructions that are associated with the most prominent EEG rhythm in the signal. These associations are arbitrary and can be modified at will, which makes the system very flexible. The system is initialized with a reference tempo (e.g., 120 beats per minute), which is constantly modulated by Hjorth's measurement of complexity.

The EEG can influence the algorithm that generates the music in a well-defined way. We implemented a statistical predictor, which uses the deducted rules to generate short musical phrases with a beginning and an end that also allows for real-time steering with EEG information. The system generates musical sequences by defining top-level structures of sequences – referred below as sentences – and methods of generating similarity-relationships or contrast-relationships between elements. Consider the following example in LISP-like notation:

```
S -> (INC BAR BAR BAR BAR BAR HALF-CADENCE 8BAR-COPY)
```

From this top-level, the system retrieves rules for selecting a valid musical building block for each symbol (INC, BAR, etc.) and a rule for incorporating the EEG information in the generative process. For example:

```
INC ->((EQUAL 'MEASURE 1)
    (EQUAL 'COMPOSER
    EEG-SET-COMPOSER))


BAR ->((CLOSE 'PITCH 'PREV-PITCH-LEADING)
    (CLOSE 'PITCH-CLASS
        'PREV-PITCH-CLASS-LEADING)
    (EQUAL 'COMPOSER
    EEG-SET-COMPOSER))
```

Above is a definition of a network that generates a valid sentence with a beginning and an end, including real-time EEG control through the variable EEG-SET-COMPOSER. The algorithm will find a musical element in the database for each of the constraint-sets that are generated above from INC and BAR, by applying the list of constraints in left-to-right order to the set of all musical elements until there are no constraints left, or there is only one musical element left. This means that some of the given constraints might not be applied.

The database of all musical elements (see Appendix for a short example) contains music from different composers, with elements tagged by their musical function such as *measure 1* for the start of a phrase, *cadence* for the end, *composer* for the name of the composer, and the special tags *pitch* and *pitch-class* that are both used for correct melodic and harmonic progression or direction. The selection process is illustrated below.

The example database in the Appendix shows the main attributes that are used to recombine musical elements. P-CLASS (for *pitch-class*) is a list of two elements. The first is the list of start-notes, transposed to the range of 0-11. The second is the list of all notes in this element (also transposed to 0-11). P is the *pitch* of the first (and highest) melodic note in this element; by matching this with the melodic note that the previous element was leading up to we can generate a melodic flow that adheres in some way to the logic of how the music should develop. The PCL (for *pitch-class leading*) elements contain the same information about the original next bar; this is used to find a possible next bar in the recombination process. Then there are the INC, BAR, and CAD elements. These are used for establishing whether those elements can be used for phrase-starts (incipient), or cadence.

Simply by combining the musical elements with the constraint-based selection process that follows from the terminals of the phrase-structure rewrite-rules, we obtain a generative method that can take into account the EEG information. This generates musical phrases with a domino-game like building block connectivity:

```
((EQUAL 'MEASURE 1)
 (EQUAL 'COMPOSER EEG-SET-COMPOSER))
```

Assuming that there are also musical elements available from composers other than SCHU, the first constraint will limit the options to all *incipient* measures from all musical elements from all composers. The second constraint will then limit the options according to the current EEG analysis to the composer that is associated with the current EEG activity, as follows:

```
((CLOSE 'PITCH 'PREV-PITCH-LEADING)
 (CLOSE 'PITCH-CLASS
      'PREV-PITCH-CLASS-LEADING)
 (EQUAL 'COMPOSER EEG-SET-COMPOSER))
```

In the given phrase structure, the rule that follows from BAR then defines the constraints put upon a valid continuation of the music. These constraints will limit the available options one by one and will order them according to the defined rule preferences. The CLOSE constraint will order the available options according to their closeness to the stored value. For example, after choosing:

```
(SCHU-1-1-MEA-1
        P-CLASS ((0 4) (0 3 4 6 7 9))
        P 76
        PCL ((2 7 11)(2 5 7 9 11))
        PL 83
        BAR INC
        CO SCHU)
```

as the beginning, PREV-PITCH-LEADING will have stored 83, and PREV-PITCH-CLASS-LEADING will have stored ((2 7 11) (2 5 7 9 11)). This will result in measure 2 and 4 being ranked highest according to both pitch and pitch-class, while measure 6 is also quite close according to pitch. This weighted choice will give a degree of freedom in the decision that is needed to generate pieces with an element of surprise. The music will not get stuck in repetitive loops, but it will find the closest possible continuation when no perfect match is available. We can still find a close match in this way if the third constraint eliminates all the obvious choices that are available; e.g., because a jump is requested to the musical elements of another composer, who might not use the same pitch-classes and pitches.

Figure 1.3 shows an example of resulting music with elements from the musical style of Schumann and Beethoven. In this example the EEG jumped back and forth, from bar to bar, between the two styles. The harmonic and melodic distances are quite large from bar to bar, but they are the optimal choices in the set of chosen elements from the two composers.

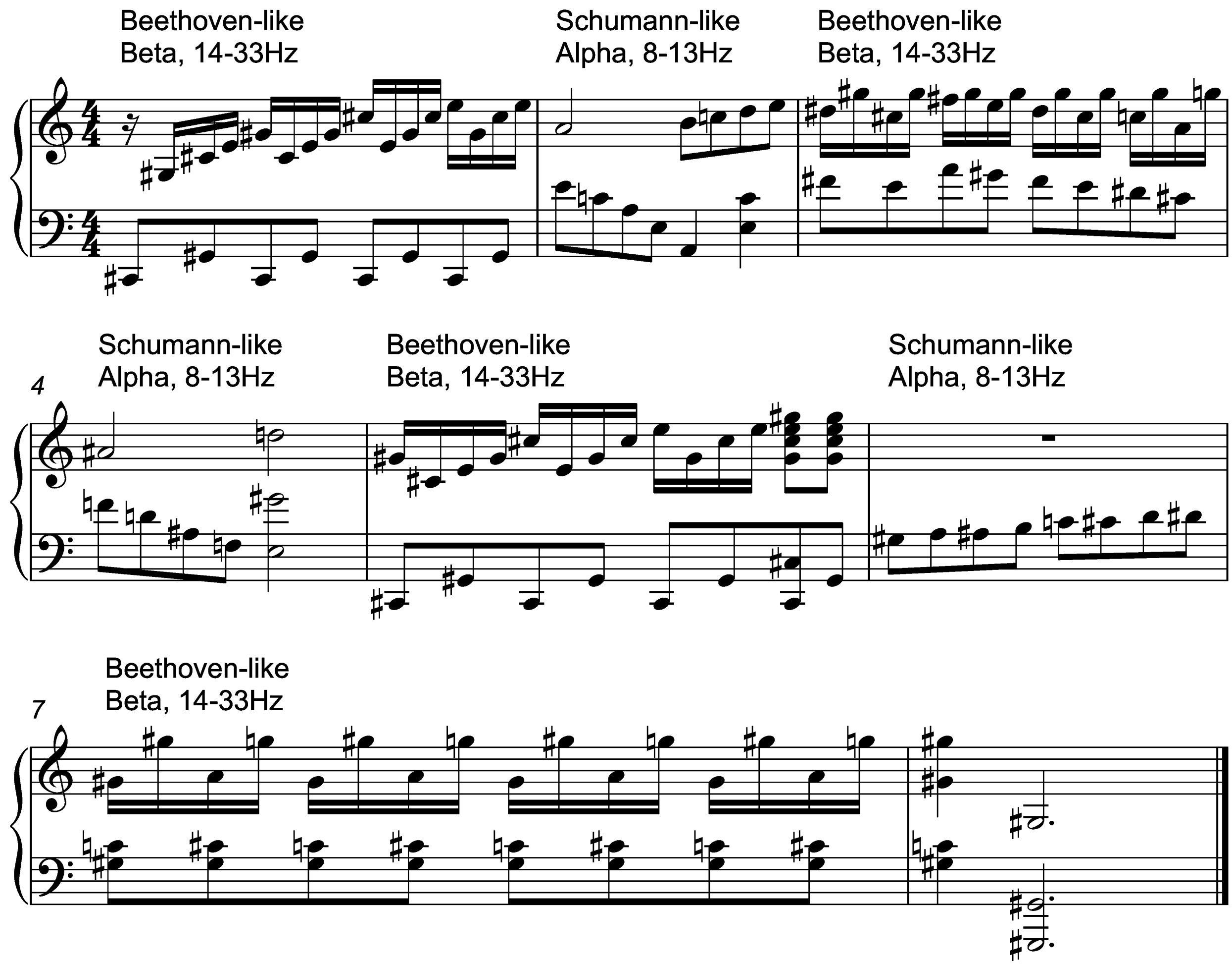


Figure 1.3: An example output where the piece alternates between the styles of Schumann and Beethoven as the EEG jumps back and forth from bar to bar between Alpha (between 8Hz and 13Hz) and Beta rhythms (between 14Hz – 33 Hz).

After a few training sections, colleagues in the laboratory were able to increase and decrease the power of their Alpha rhythms in relation to the Beta rhythms practically at will, therefore being able to voluntarily switch between two styles of music. We noticed that the signal complexity measurement tended to be higher when Beta rhythms were more prominent in the signal: the music in the style of Beethoven tended to be played slightly louder and faster than pieces in the style of Schumann.

At this point, I went on to address my second dreamed scenario: Would it be possible to build a BCMI system for a person with locked-in syndrome to make music?

As it turned out, after a critical evaluation of our system, informed by opinions and advice from health professionals and music therapists working with disable patients, I concluded that the BCMI-Piano was nor robust nor portable enough to be taken from the laboratory into the real world. The system comprised two laptops, two bulky hardware units for EEG amplification and too many dangling cables. Moreover, the skills required for placing the electrodes on the scalp and run the various components of the system were time-consuming and far beyond the typical skills of a music therapist or carer. Also, it was generally agreed that, from the point of view of a user, the system would not give the feeling that they were really playing the piano, or creating music. After all, it is the computer who composes the music; the user only switch between two modes of operation. I was advised that I should try to devolve the creative process to the user even if it is to create very simple music. I soon realised that this would require more options for control.

1.5 SSVEP-Music System

I teamed up with music therapist Wendy Magee and her colleagues at Royal Hospital for Neuro-disability, London, to develop a new system aimed at a trial with a Locked-in Syndrome patient, henceforth referred to Tester M. Tester M's only active movements following a stroke include eye movements, facial gestures and minimal head movements. She retained full cognitive capacity.

The two challenges that we had to address in this design were to devolve the creative process to the user and provide more options for control. Technically, a solution for the former would depend on the solution for the latter. Hence we started by focusing on increasing the number of controls. To this end, we shifted from using EEG rhythms to adopting an evoked potential approach based on the SSVEP method that I mentioned earlier.

The new SSVEP-Music system was implemented in collaboration with Joel Eaton, a post-graduate research student at ICCMR, and John Wilson and Ramaswamy Palaniappan[2], of University of Essex (Miranda et al. 2011). Thanks to the SSVEP approach, we were able to implement four switches for control, as opposed to only one in BCMI-Piano. Moreover, each switch acted as a potentiometer for continuous control.

Figure 1.4 shows a photograph of a subject using the system. The monitor on the left hand side in Figure 1.4 shows four images. These images flash at different frequencies, reversing their colours. Each image is associated with a musical process. Therefore, the system executes four different tasks, which the user can select by staring at the respective flashing image.

The SSVEP control signal can be used to generate the melody in a variety of ways, which can be customized. We provided a number of configurations that can be loaded into the system. For instance, suppose that the top image, shown on the monitor of the left hand side of the picture in Figure 1.4, is associated with the task of generating a melody from an ordered set of five notes (Figure 1.5). Let us say that this image flashes at a rate of 15 Hz. When one stares at it, the system detects that the subject is staring at this image and sends a command to generate the respective melody. The SSVEP paradigm is interesting because the more the subject attends to the flashing image, the more prominent is the amplitude of the EEG component corresponding to the brain's response to this stimulus. This produces a varying control signal, which is used to produce the melody and provide a visual feedback to the user: the size of the image increases or decreases in function of this control signal. In this way we can steer the production of the notes by the intensity to which one attends to the respective image. One can bring the index down by looking away and bring the index up by staring at it again. Fine control of this variation can be

[2] Currently at University of Wolverhampton.

achieved with practice; e.g., to repeat a single note many times, or repeat a sub-group of notes, and so on. Each of the images could correspond to a distinct note sequence, and so on. This scheme opens up many possibilities for music control.

Figure 1.4: Photograph of a subject operating the system.

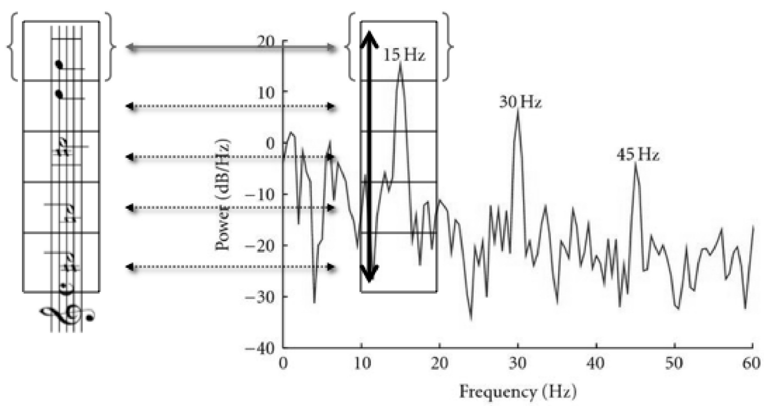


Figure 1.5: Five bandwidths are established for the varying control signal, which are associated to the indices of an array of musical notes.

The SSVEP-Music system has proved to be rather successful because one can almost immediately produce musical notes with very little, or no training, simply by looking intently at the different images. As one learns to modulate the extent to which he or she is attending the images, more sophisticated musical control can be achieved, as if learning to play a musical instrument: the more one practices the better one becomes at it.

Terster M trialled the system during a two-hour session. Being familiar with eye gaze technology for her alternative communication system, Tester M grasped the concept quickly and rapidly demonstrated her skills at playing the system with minimal practice. She was able to vary the intensity of her gaze, thus changing the amplitude of her EEG and vary the consequent melodic and dynamic output. Personal correspondence with Tester M following this trial communicated that she had enjoyed considerably using the system and that “...it was great to be in control again”. This feedback is immensely gratifying and very encouraging. The possibilities for applying the system within group settings is immediately apparent and an exciting prospect for people with limited opportunities for participating as an equal partner in a group.

We are aware that some aspects of the system still require further refinement to make it more practical and viable for clinical applications. For instance, the frequency rate at which the images flash may limit using the system with people known to have epilepsy, a possible consequence following acquired brain injury.

The time required to place the electrodes on the scalp was reduced considerable: only three electrodes are required here. However, SSVEP-Music requires calibration to match the sensitivity of the system with the user’s visual cortex response to the flashing images. This is outside typical clinical skills and can be time-consuming. The downside is that this calibration needs to be done before a session begins. Although this could be overcome with training, increasing the time burden of a clinical session is known to be a preventative factor influencing the uptake of technology by the health care sector.

Nevertheless, despite all the limitations, we succeeded in providing more control options and devolving the creative process to the user. And more importantly, we demonstrated that is it indeed possible to build a BCMI system for a person with locked-in syndrome to make music.

1.6 Discussion: Moving Forwards

In addition to the limitations discussed above, I am currently addressing two technical challenges, which I believe are important to move research into BCMI forwards:

a) Discovery of meaningful musical information in brain signals for control beyond the standard EEG rhythms.

b) Design of powerful techniques and tools for implementing flexible and sophisticated on-line generative music systems.

In order to the address the former I have been conducting a number of brain scanning experiments aimed at gaining a better understanding of brain correlates of music cognition, with a view on discovering patterns of brain activity suitable for BCMI control. In the following section we report on the results of two experiments: one on listening imagination and another on musical tonality.

As for the second challenge, it is important to ensure that the BCMI system offers an adequate musical repertoire or challenge to maintain the engagement of people who may have vastly sophisticated musical experiences and tastes. I have been looking into expanding the generative capabilities of the BCMI-Piano music algorithm by means of constraint satisfaction programming techniques.

1.7 Active Listening Experiment

This experiment was developed with Alex Duncan, a former postgraduate research student, and Kerry Kilborn and Ken Sharman, at University of Glasgow. The objective of the experiment was to test the hypothesis that it is possible to detect information in the EEG indicating when a subject is engaged in one of two mental tasks: *active listening* or *passive listening* (Miranda et al. 2003). In this context, the active listening task is to replay the experience of hearing some music, or part of that music, in the mind's ear. Conversely, passive listening is to listen to music without making any special mental effort. In day-to-day life experience we are likely to be listening passively if we are relaxing to peaceful music or engaged in some other task whilst listening to music in the background.

Three non-musicians, young males, with age ranging between 18 and 25 years old, participated in the experiment, which was divided into six blocks of trials, giving the participants the chance to relax. Each trial lasted for eight seconds and contained two parts: a rhythmic part, lasting for the entire trial, and a melodic riff part, lasting for the first half of the trial. A riff is a short musical passage that is usually repeated many times in the course of a piece of music. It was during the second half of each trial that the mental task was performed. The rhythmic part comprised four repetitions of a 1-bar rhythm loop. Two repetitions a 1-bar riff loop starting at the beginning of the trial and terminating halfway through were superimposed on the rhythmic part (Figure 1.6).

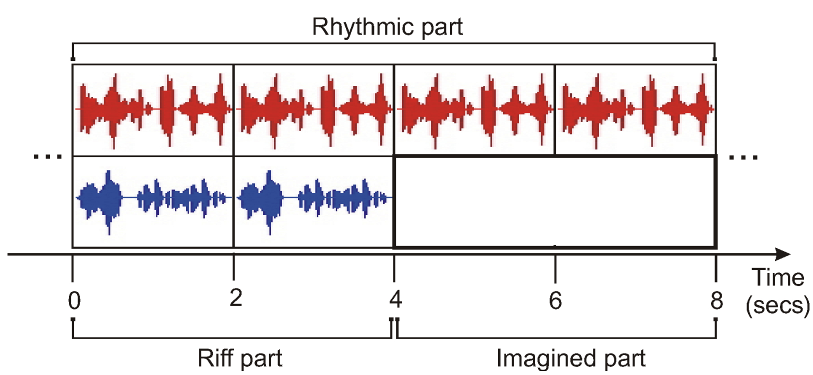


Figure 1.6: Participants listened to 4-bar trials containing a looped riff lasting for 2 bars.

In total, there were 15 unique riff loops: five played on a synthesized piano, five using an electronic type of timbre, and five on an electric guitar. The music was in the style of a pop dance tune at 120 beats per minute, four beats per bar. The background rhythm looped seamlessly for the entire duration of each trial block. Blocks were named after the task the participant was instructed to perform on that block, and they were ordered as shown in Table 1.1. Each of the 15 riff parts was presented four times in each block in random order.

Block	Subject 1	Subject 2	Subject 3
1	active	passive	counting
2	passive	counting	active
3	counting	active	passive
4	active	passive	counting
5	passive	counting	active
6	counting	active	passive

Table 1.1: The experiment was divided into six blocks of trials. Blocks were named after the mental task the subjects were instructed to perform.

Participants were instructed to perform one of three mental tasks while listening to a continuous sequence of trials:

a. Active listening: listen to the looped riff that lasts for 2 bars, then immediately after it finishes, imagine that the riff continues for another 2 bars until the next trial begins.

b. Passive listening: listen to the entire 4-bar trial with no effort; just relax and focus on the continuing background part.

c. Counting task: listen to the looped riff that lasts for 2 bars, then immediately after it finishes, mentally count the following self-repeating sequence of numbers (i.e., mentally spoken): 1, 10, 3, 8, 5, 6, 7, 4, 2, 1, 10, and so forth.

The classification task was to determine the class of 2-second multi-channel EEG segments, where class(1) = active listening, class(2) = passive listening and class(3) = counting task.

The counting task was included as a control task to determine whether the EEG features that might allow for the differentiation between the imagery and relaxed listening tasks are not merely a function of a concentrating versus a non-concentrating state of mind.

Only the last four seconds (i.e., the second half of each trial) were considered for analysis. These 4-second long segments were further divided into two 2-second long segments. Thus each trial yielded two segments. There were 120 trials for each of the three conditions and each subject produced a total of 720 segments: 240 segments for each condition. The data is randomly partitioned into training set and testing set with split ratio of 9:1, resulting in 648 training segments and 72 testing segments.

We employed a linear auto-regression algorithm to represent the EEG data in a compressed form in terms of estimations of spectral density in time (Anderson and Sijercic 1996, Peters at al. 1997). Then, a classic single hidden-layer static neural network (Multi-Layer Perceptron), with variable number of hidden units and up to three output units, was used for the classification task. The network was trained in batch mode for 50 epochs, using a scaled conjugate gradient algorithm, as described by Bishop (1995). The data was divided into two sets: a training set *E* and a test set *T*. The training set *E* was used to train the neural network to recognise the mental tasks of the elements that were left in *T*. In total, there were 768 inputs to the network. The network was reset, re-trained and re-assessed 10 times with different permutations of training and testing segments.

Classifications were made between 2-second long multi-channel segments belonging to pairs of conditions (for 2-way classification) and to all three conditions (for 3-way classification). The average classification scores, including confidence limits and standard deviation, for each subject are shown in Table 1.2.

Remarkably, the classification scores are above 90% accuracy. We acknowledge that these results may not sound statistically robust because the experiment involved only three subjects. Nevertheless, they encouraged us to work towards the implementation of a BCMI on the assumption that the system would be capable to establish if a subject is actively listening to music, or passively listening to it without any special mental effort. This notion is supported by a number of reports on experiments looking into musical imagination; e.g., (Meister et al. 2004, Limb and Braun 2008, Miranda et al. 2005, Petsche et al. 1996).

Subject	Classification task	Mean	Min.	Max.	Deviation	Confidence
1	active × passive	0.998	0.979	1.000	0.007	+/– 0.007
	active × counting	0.996	0.979	1.000	0.009	+/– 0.009
	passive × counting	0.994	0.979	1.000	0.010	+/– 0.010
	active × passive × counting	0.998	0.958	1.000	0.015	+/– 0.016
2	active × passive	0.994	0.979	1.000	0.010	+/– 0.010
	active × counting	0.973	0.896	1.000	0.031	+/– 0.032
	passive × counting	0.954	0.896	1.000	0.038	+/– 0.039
	active × passive × counting	0.951	0.903	0.986	0.023	+/– 0.024
3	active × passive	0.973	0.958	1.000	0.014	+/– 0.014
	active × counting	0.992	0.979	1.000	0.011	+/– 0.011
	passive × counting	0.994	0.958	1.000	0.014	+/– 0.014
	active × passive × counting	0.985	0.958	1.000	0.015	+/– 0.016

Table 1.2: Average classification scores for the Active Listening experiment.

1.7.1 Towards an Active Listening BCMI

The results from the above experiment encouraged me to look into the possibility of developing a BCMI whereby the user would be able to affect the music being generated in real-time by focusing attention to specific constituents of the music. I designed a prototype, which produces two tracks of music of the same style of the music stimuli that was devised for the experiment: it comprises a rhythmic track and a solo track, which is generated by means of algorithms that transforms a given riff; they can transpose it, change rhythm, add a note, remove a note, play the riff backwards, and so on.

Firstly, the neural network is trained to recognise when the incoming EEG corresponds to active or passive listening, as described in the experimental procedure. Needless to say, the person who controls the music here should be the same as the one who's EEG was used to train the system. The system works as follows: the rhythmic part is continuously played and a riff is played sporadically; an initial riff is given by default. Immediately after a riff is played, the system checks the subject's EEG. If it detects active listening behaviour, then the system applies some transformation on the riff that has just been played and plays it again. Otherwise it does not do anything to the riff and waits for the subject's EEG response to the next sporadic riff. Sporadic riffs are always a repetition of the last played riff; in other words, it does not change until the system detects active listening behaviour.

In practice I found it difficult to reliably detect active listening behaviour when a user is consciously trying to change the riffs online. Either, more efficient EEG signal processing algorithms need to be employed, or the paradigm is flawed. Or both. More work is required to address this problem.

1.8 Neural Processing of Tonality Experiment

In (Miranda et al. 2008) and (Durrant et al. 2009) I introduced a functional Magnetic Resonance Imaging (fMRI) study of tonality, which I developed with Simon Durrant, a former ICCMR research fellow, and Andre Brechmann, of the Leibniz Institute for Neurobiology, Germany. The objective of this experiment was to gain a better understanding of the neural substrates underlying the perception of tonality, with a view on developing a method to harness their behaviour to control a BCMI. We looked for differences in neural processing of tonal and atonal stimuli, and also for neural correlates of distance around the circle-of-fifths, which describes how close one key is to another.

Tonality is concerned with the establishment of a sense of key, which in turn defines a series of expectations of musical notes. Within Western music, the octave is divided into twelve equal semitones, seven of which are said to belong to the scale of any given key. Within these seven tones, the first (or lowest) is normally referred to as the fundamental note of the chord, and the one that the key is named after. A sense of key can be established by a single melodic line, with harmony implied, but can also have that harmony explicitly created in the form of chord progressions. Tonality defines clear expectations, with the chord built on the first tone (or degree) taking priority. The chords based on the fourth and fifth degrees also are important because their constituent members are the only ones whose constituent tones are entirely taken from the seven tones of the original scale, and occurring with greater frequency than other chords. The chord based on the fifth degree is followed the majority of the time by the chord based on the first degree. In musical jargon, this is referred to as a dominant-tonic progression. This special relationship also extends to different keys, with the keys based on the fourth and fifth degrees of a scale being closest to an existing key by virtue of sharing all but one scale tone with that key. This gives rise to what is known as the circle-of-fifths, where a change - or modulation - from one key to another is typically to one of these other closer keys (Shepard 1982). Hence we can define the closeness of keys based on their proximity in the circle of fifths, with keys whose first degree scale tones are a fifth apart sharing most of their scale tones, and being perceived as closest to each other (Durrant et al. 2009).

Sixteen volunteers, 9 females and 7 males, with age ranging between 19 and 31 years old and non-musicians, participated in the experiment. Five experimental conditions were defined: *distant*, *close*, *same*, *initial* and *atonal* (that is, no key) conditions, respectively. As a result of the contiguity of groups, the first stimulus in each group followed the atonal stimulus in the previous group (except for the initial group), which was defined as the *initial* condition. The *distant* and *close* conditions therefore defined changes from one key to another (distant or close respectively), whereas the *same* condition defined no change of key (i.e., the next stimulus was in the same key). The *atonal* condition defined a lack of key, which was included here as a control condition. The stimuli were ordered such that all tonal stimuli were used an equal number of times, and the conditions appeared in all permutations equally in order to control for order effects.

Each stimulus consisted of 16 isochronous events lasting 500 milliseconds each, with each stimulus therefore lasting 8 seconds without gaps in between. Each event consisted of a chord recognised in Western tonal music theory, with each chord being in root position (i.e., the lowest note of the chord is also the fundamental note). The sense of key, or lack of it, was given by the sequence of 16 chords, rather than by individual chords. For a single run, stimuli were ordered into twenty-four groups of three stimuli with no gaps between stimuli or groups. The first stimulus in each group was always a tonal stimulus presented in the home key of C major, the second was always a tonal stimulus that could either be in the distant key of F# major, the closely-related key of G major, or the same key of C-major. In order to reset the listener's sense of relative key, the third stimulus in each group was always an atonal stimulus; that is, the chord sequences without any recognisable key (Figure 1.7).

Figure 1.7: Musical scores representing the stimuli used in the tonal experiment. At the top stave is the tonal stimulus in the key of C major, which is the initial and same conditions, respectively. In the middle is the stimulus in the key of F# major, which is the distant condition. At the bottom is the stimulus in no obvious key.

In order to draw the attention of the participants to the tonal structure of the stimulus stream, the behavioral task in the scanner was to click the left mouse button when they heard a change to a different key (*distant*, *close* and *initial* conditions), and right-click the mouse button when they heard a change to no key (*atonal* condition). As the participants were non-musicians, the task was explained as clicking in response to a given type of change so as to avoid misunderstandings of the meaning of the terms 'tonal', 'atonal' and 'key'. That is, they were instructed to indicate any change from one key to another by clicking on the left button of a mouse, and a change towards a sequence with no key by clicking on the right button. Subjects were given an initial practice period in order to ensure that they understood the task.

The results of the behavioural taks are shown in Table 1.3, which gives the percentage of trials that contained a left- or right-click for each condition. Second-level one-way analysis of variance (ANOVA) was performed for the left-click and right-click results respectively across all participants. Conditions *distant*, *close* and *initial* had a significantly higher number of left-click responses than for conditions *same* and *atonal*. Conversely, the *atonal* condition had a significantly higher amount of right mouse clicks than for *distant*, *same* and *atonal* conditions. These results confirm that the participants were able to perform the behavioural task satisfactorily and show that the participants had some awareness of the tonal structure of the stimuli.

Condition	Left Click	Right Click
Distant	89.453	11.328
Close	83.594	0.7812
Same	26.563	3.5156
Initial	68.62	4.2969
Atonal	14.193	83.984

Table 1.3. Behavioral results, showing the percentage of trials that contained a left- or right-click aggregated over all participants in the experiment.

As for the fMRI scanning, functional volumes were collected with 3 Tesla scanner using echo planar imaging. A more detailed description of the data acquisition procedures and analysis methods are beyond the scope of this chapter. In summary, each stimulus block lasted 8 seconds and was immediately followed by the next stimulus block. Analysis was performed with a General Linear Model (GLM) (Friston et al. 2006).

Group analysis revealed a cluster of fMRI activation around the auditory cortex (especially in the left hemisphere) showing a systematic increase in BOLD (Blood-Oxygen-Level Dependent) amplitude with increasing distance in key. We have found a number of significant active neural clusters associated with the processing of tonality, which represent a diverse network of activation, as shown in Table 1.4 and Figure 1.9.

Anatomical Name	X	Y	Z	Cluster
(1) Left Transverse Temporal Gyrus	-51	-18	11	981
(2) Right Insula	36	17	13	948
(3) Right Lentiform Nucleous	24	-1	1	750
(4) Right Caudate	14	-4	22	1443
(5) Left Anterior Cingulate	-1	41	11	2574
(6) Left Superior Frontal Gyrus	-12	50	36	2241
(7) Right Transverse Temporal Gyrus	51	-17	10	1023

Table 1.4: Anatomical results of GLM analysis contrasting conditions with and without a key change. These active clusters preferentially favour key change stimuli. X, Y and Z are Talairach coordinates for plotting scans onto a standard template after normalization of brain size and shape across the subjects.

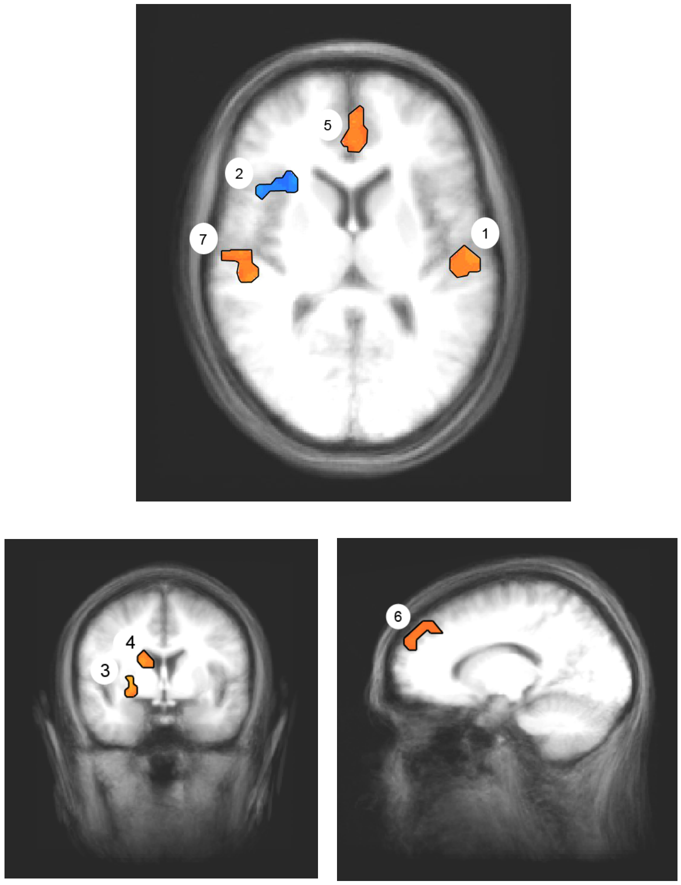
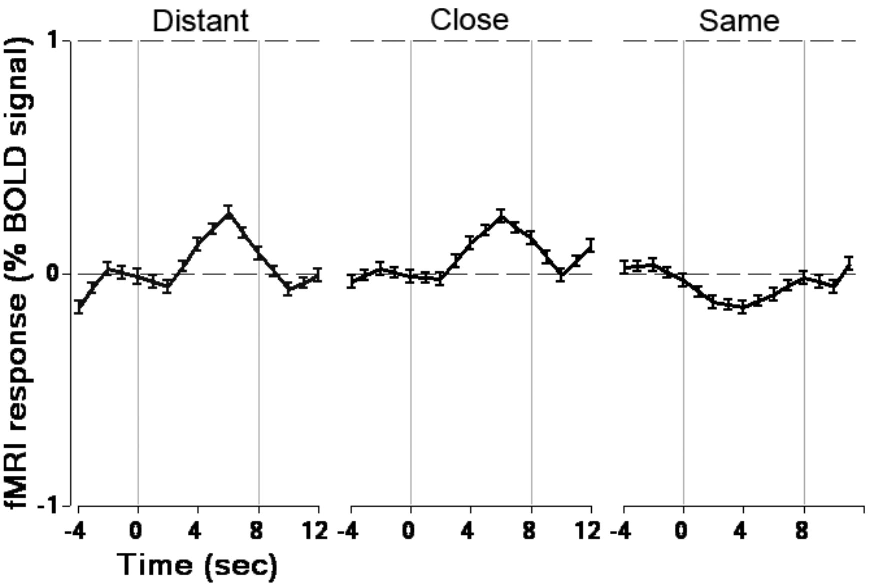


Figure 1.8: Examples of clusters of activation for the contrast distant and close key vs. same key, including bilateral activation of transverse temporal gyrus for which the activation curves are shown in Table 1.4.

We note the strong presence of medial structures, in particular *cingulate cortex* (label 5 in Figure 1.8 and Table 1.4) and *caudate nucleus* (label 4 in Figure 1.8 and Table 1.4) in response to key changes. Also significant is the bilateral activation for key changes of the *transverse temporal gyrus* also known as Heschl's gyrus (labels 1 and 7 in Figure 1.8 and Table 1.4), which contains the primary auditory cortex. The activation curves for the bilateral activation of the *transverse temporal gyrus* show strongest activity for the distant key changes, slightly less, but still significant activity for the close key changes, and much less activity for no key changes (Figure 1.9). It should be emphasized that this occurred across a variety of different stimuli, all of equal amplitude and with very similar basic auditory features, such as envelope and broad spectral content. Both left and right *transverse temporal gyri* showed very similar response curves highlighting the robust nature of these results. This might suggest that these areas may not be limited to low-level single note processing as commonly thought, but also are involved in some higher-order sequence processing. This significant for my research as it could constitute a potential source of control information for a BCMI, associated with tonality and modulation. However, more testing needs to be developed in order to probe this.



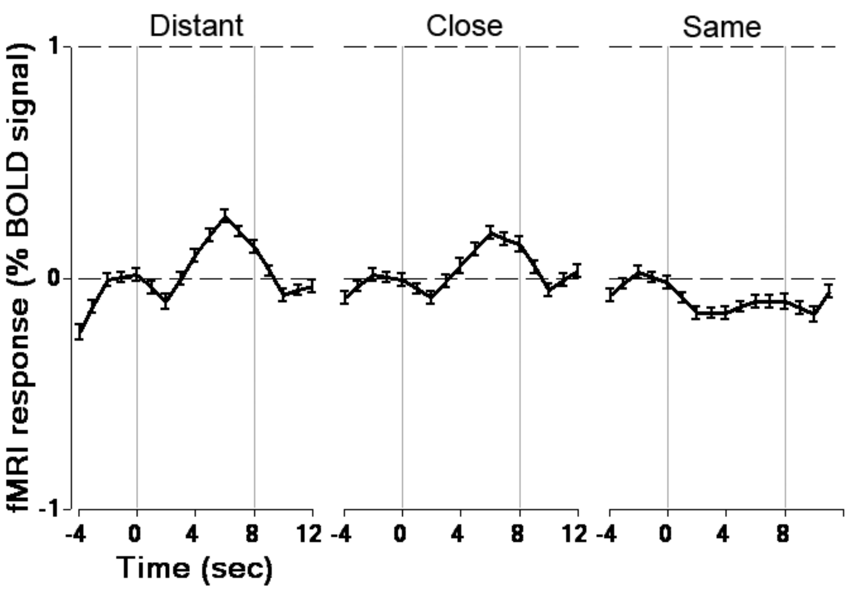


Figure 1.9: Activation curves in left (top graph) and right (bottom graph) transverse temporal gyri for *distant* condition (plot on the left side), *close* condition (plot in the middle) and *same* condition (plot on the right side).

1.8.1 Towards a BCMI for Controlling Tonality

The results of the tonality experiment suggest that it might indeed be possible to design a BCMI controlled with auditory cortex activity correlated to tonality. However, despite ongoing attempts at using fMRI for BCI (Weiskopf et al. 2004), fMRI still is impractical for this purpose: fMRI scanning is simply too expensive to run, the equipment is not portable, and the health and safety implications for usage outside strict laboratory conditions are fiendishly burdensome. Moreover, fMRI scanners produce noise during the scan, which makes it inconvenient for a musical application. We are currently working on detecting in the EEG equivalent activations in auditory cortex as we detected in the fMRI scans.

In the meantime, I have been developing generative music systems suitable for control with information representing cortical activations of tonal processing. I teamed up with Torsten Anders, a former research fellow at ICCMR, to implement a prototype that generates chords sequences automatically, in the style of the ones used as stimuli for the tonality experiments (Miranda et al. 2008).

We adopted a computational paradigm referred to as *constraint satisfaction problem* to implement a generative music system that generates sequences of chord progressions in real-time (Anders and Miranda 2011, Anders and Miranda 2010). The input to the system is a stream of pairs of hypothetic brain data, which controls higher-level aspects of chord progressions. The first value of the pair specifies whether a progression should form a cadence, which clearly expresses a specific key (cadence progression), or a chord sequence without any recognizable key (key-free progression). Additionally, if the next progression is a cadence progression, then the key of the cadence is specified by the second value of the pair.

Each chord progression (Figure 1.10) consists of n major or minor chords (in the example n = 16). Different compositional rules are applied to cadence and key-free progressions. For instance, in the case of a cadence, the underlying harmonic rhythm is slower than the actual chords (e.g., one harmony per bar), and all chords must fall in a given major scale. The progression starts and ends in the tonic chord, and intermediate root progressions are governed by Schoenberg's rules for tonal harmony (Schoenberg 1986). For a key-free, atonal progression, the rules established that all 12 chromatic pitch classes are used. For example, the roots of consecutive chords must differ and the set of all roots in the progression must express the chromatic total. In addition, melodic intervals must not exceed an octave. A custom dynamic variable ordering scheme speeds up the search process by visiting harmony variables (the root and whether it is major or minor), then the pitches' group (or classes) and finally the pitches themselves. The value ordering is randomized, so the system always produces different results.

Figure 1.10: Extract from a sequence of chord progressions generated by our constraints-based generative system. In this case the system produced a sequence in C major, followed by a sequence in no particular key and then a sequence in A major.

As it is, the generative system design assumes that subjects would be able to produce the required control information in some way or another. In practice, however, it is unlikely that subjects would learn to produce bilateral activations of transverse temporal gyrus simply by imagining tonal progressions. The challenge here is to establish effective ways to embed in a realistic system design the theoretical understanding of neural correlates of tonal processing and generative musical algorithms. The research continues.

1.9 Concluding Remarks

There has been a tremendous progress in the field of BCI in the last decade or so, in particular on EEG signal processing aspects, which is the focus of a number of chapters in this volume. BCMI research is obviously benefiting from this progress. From the experienced I have gained with trialing the SSVEP-Music with a patient in a hospital setting, I learned the hard way that the hardware aspect of BCI lags behind the more theoretical advances in the field. The EEG electrode technology that is currently commercially available is adequate for medical diagnosis, but not for wearing on a more frequent and ad hoc basis. Dangling wires, electrodes cap, gel, required technical support for handling, and so on need to disappear from the equation in order to pave the way for BCMI systems into the real-world of health care. The equipment must be simple to switch on, setup and operate. Fortunately, the electronics industry is making continuing progress at this front: wireless electrodes that do not need gel are beginning to emerge in the market and more mobile, less conspicuous, good quality EEG amplifiers are becoming available – albeit good quality equipment still is not generally affordable.

From the musical side, my ICCMR team and I are continuously paving the way for the development of effective music algorithms for BCMI. I believe that an approach combining the technique developed for the BCMI-Piano and the constraints-based system built after the tonality experiment is a viable way to proceed and I will continue working towards this goal.

The issue of harnessing the EEG for BCMI control with signals correlated to music cognition remains unresolved. It turns out that the most effective control methods are those that are not at all related to music, such as for instance the SSVEP method. It is questionable whether the types of music cognition I touched upon in this chapter are the way forward or not. Much research is needed in order to make progress at this front.

1.10 Questions

1. Is voluntary control always necessary in BCI? Give some examples to illustrate your answer.

2. What is the difference between these three approaches of BCI control: conscious effort, operational conditioning and evoked potentials?

3. How does BCMI-Piano regulate the tempo and loudness of the music?

4. Why was the BCMI-Piano system not suitable for trial in a clinical context?

5. What are the differences between the SSVEP-Music and BCMI-Piano systems? Elaborate on advantages and disadvantages of both systems.

6. How many degrees of freedom are afforded by the SSVEP-Music system?

7. The chapter described a method to generate a melody using the SSVEP control signal. Could you envisage how this be done differently?

8. Why was the counting task included in the active listening experiment?

9. Given the state of the art of fMRI technology, would it be viable to build an fMRI-based BCMI?

10. How can fMRI technology help to advance research into the design of more sophisticated EEG-based BCMI systems?

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Appendix: Data Base of Musical Elements

An excerpt from a database of musical elements where: **CO** = composer (SCHU = Robert Schumann.), **P-CLASS** = pitch class, **P** = pitch, **PCL** = pitch-class leading, **PL** = pitch leading and **TPE** = type.

ID SCHU-1-1-CAD
CO SCHU
P-CLASS ((0 2 7)(0 2 4 5 7 11))
P 74
PCL ((0 4 9)(0 2 4 5 7 9 11))
PL 76
TPE CAD

ID SCHU-1-1-MEA-6
CO SCHU
P-CLASS ((5 9)(0 5 7 9))
P 81
PCL ((0 2 7)(0 2 4 5 7 11))
PL 74
TPE BAR

ID SCHU-1-1-MEA-5
CO SCHU
P-CLASS ((0 4)(0 4 7))
P 76
PCL ((5 9)(0 5 7 9))
PL 81
TPE BAR

ID SCHU-1-1-MEA-4
CO SCHU
P-CLASS ((0 4)(0 3 4 6 7 9))
P 83
PCL ((0 4)(0 4 7))
PL 76
TPE BAR

ID SCHU-1-1-MEA-3

CO SCHU
P-CLASS ((0 4)(0 3 4 6 7 9))
P 76
PCL ((2 7 11)(2 5 7 9 11))
PL 83
TPE BAR

ID SCHU-1-1-MEA-2
CO SCHU
P-CLASS ((2 7 11)(2 5 7 9 11))
P 83
PCL ((0 4)(0 3 4 6 7 9))
PL 76
TPE BAR

ID SCHU-1-1-MEA-1
CO SCHU
P-CLASS ((0 4)(0 3 4 6 7 9))
P 76
PCL ((2 7 11)(2 5 7 9 11))
PL 83
TPE INC